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Classification of Posture Maintenance Data with Fuzzy Clustering Algorithms

Final Report

James C. Bezdek
The University of West Florida

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The RICIS Concept

The University of Houston-Clear Lake established the Research Institute for Computing and Information Systems (RICIS) in 1986 to encourage the NASA Johnson Space Center (JSC) and local industry to actively support research in the computing and information sciences. As part of this endeavor, UHCL proposed a partnership with JSC to jointly define and manage an integrated program of research in advanced data processing technology needed for JSC's main missions, including administrative, engineering and science responsibilities. JSC agreed and entered into a continuing cooperative agreement with UHCL beginning in May 1986, to jointly plan and execute such research through RICIS. Additionally, under Cooperative Agreement NCC 9-16, computing and educational facilities are shared by the two institutions to conduct the research.

The UHCL/RICIS mission is to conduct, coordinate, and disseminate research and professional level education in computing and information systems to serve the needs of the government, industry, community and academia. RICIS combines resources of UHCL and its gateway affiliates to research and develop materials, prototypes and publications on topics of mutual interest to its sponsors and researchers. Within UHCL, the mission is being implemented through interdisciplinary involvement of faculty and students from each of the four schools: Business and Public Administration, Education, Human Sciences and Humanities, and Natural and Applied Sciences. RICIS also collaborates with industry in a companion program. This program is focused on serving the research and advanced development needs of industry.

Moreover, UHCL established relationships with other universities and research organizations, having common research interests, to provide additional sources of expertise to conduct needed research. For example, UHCL has entered into a special partnership with Texas A&M University to help oversee RICIS research and education programs, while other research organizations are involved via the "gateway" concept.

A major role of RICIS then is to find the best match of sponsors, researchers and research objectives to advance knowledge in the computing and information sciences. RICIS, working jointly with its sponsors, advises on research needs, recommends principals for conducting the research, provides technical and administrative support to coordinate the research and integrates technical results into the goals of UHCL, NASA/JSC and industry.

Classification of Posture Maintenance Data with Fuzzy Clustering Algorithms

Final Report

Preface

This research was conducted under auspices of the Research Institute for Computing and Information Systems by Dr. James C. Bezdek of the Institute for Interdisciplinary Study of Human and Machine Cognition at the University of West Florida. Dr. Terry Feagin served as RICIS research coordinator.

Funding has been provided by the Information Technology Division, Information Systems Directorate, NASA/JSC through Cooperative Agreement NCC 9-16 between the NASA Johnson Space Center and the University of Houston-Clear Lake. The NASA technical monitor for this activity was James A. Villarreal, of the Software Technology Branch, Information Technology Division, Information Systems Directorate, NASA/JSC.

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WITH FUZZY CLUSTERING ALGORITHMS

FINAL REPORT

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Neural Networks Program
Software Technology Branch, JT4
Houston, Texas 77058

Submitted by : **The University of West Florida**
Institute for Interdisciplinary Study of Human and Machine Cognition
Division of Computer Science
11000 University Parkway
Pensacola, FL 32514

Date Submitted : January 31, 1992

Principal Investigator : James C. Bezdek Date : 1/31/92
Dr. James C. Bezdek : Nystul Professor : Division of Computer Science
University of West Florida, Pensacola, FLA 32514 : Tel. (904) 474-2784

Faculty Collaborator: Patrick O. Bobbie Date : 1/31/92
Dr. Patrick O. Bobbie : Assoc. Professor : Division of Computer Science
University of West Florida, Pensacola, FLA 32514 : Tel. (904) 474-2784

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About the Cover

Warriors in all ancient cultures were trained to assume the defensive stance shown on our cover illustration. It has always been felt that this position, with the left foot advanced and right foot firmly planted, secures maximum *postural stability* at the point of attack. This belief is based on the fact that most warriors, even today, are right-handed.

Executive Summary

Sensory inputs from the visual, vestibular and proprioreceptive systems are integrated by the central nervous system to maintain postural equilibrium. Sustained exposure to microgravity causes neurosensory adaptation during spaceflight, which results in decreased postural stability until readaptation occurs upon return to the terrestrial environment. Data which simulate sensory inputs under various sensory organization test (SOT) conditions have been collected in conjunction with Johnson Space Center postural control studies using a tilt-translation device (TTD). The University of West Florida has applied the fuzzy c-means (FCM) clustering algorithms to this data with a view towards identifying various states and stages of subjects experiencing such changes.

Data for this study were supplied by NASA/JSC via Tom Collins, Krug Life Sciences. The data were collected from five subjects both before (pre) and after (post) exposure to the TTD platform in SOT6. A third set of (control) data were also used in this study, namely, (pre) test data for SOT1. Each pair of classes were used to "train" an (FCM) nearest prototype classifier; subsequently, the data were (re)submitted to this classifier in an attempt to identify and characterize cluster substructure in a mixed ensemble of TTD data scenarios. Our main conclusions are as follows:

Feature Analysis. The features that worked best with the Fuzzy c-Means clustering algorithm among the ones supplied were the triple (Channel 3, Channel 7, Channel 8) = (Shear Force Transducer, Shoulder Sway, Hip Sway). Other sets, and subsets of these three gave much worse results, as did various linear combinations of the features given. In our experience the four EMG signals possessed no useful information for discrimination between pairs of tests.

Time Step Analysis. Our computations indicate that when the data for different testing conditions are treated uniformly and collectively across time, there is much more difficulty in separation than when the differential approach reported here is taken. There are some time subintervals that seem to yield data with much better separability than others.

Pooling Data. Our experiments indicate that pooling data across subjects considerably degrades their separability. Although the number of subjects (5) in our pool was small, our inference from these calculations is that while separability can be achieved for a particular subject, good performance from a fixed classifier across a wide variety of subjects seems very unlikely. This is not surprising, in view of the wide variability humans have at responding to essentially identical tasks (postural adaptation in this case).

Subjects. Some idea of the relative stability and response of each of the five subjects to the tests they took can be gained from our results. This seems like a potentially important and useful finding- viz., that the use of Fuzzy c-Means might enable one to *rank* the ability of different space travellers at postural adaptation tasks. Subsequently, such results might be used to design different individualized approaches to re-entry training for different astronauts.

Algorithms. With the limited resources at our disposal, it was impossible to extensively test Fuzzy c-Means as regards different norms, initializations, termination criteria and the like. However, the success of FCM reported herein suggests that investigations of these and related issues and algorithms might lead to better understanding of adaptation mechanisms for postural adaptation than those currently known.

$\mathbf{A}$ = is any positive definite (s x s) matrix; and (5d)

$\|\mathbf{x}_k - \mathbf{v}_i\|_A = (\mathbf{x}_k - \mathbf{v}_i)^T A (\mathbf{x}_k - \mathbf{v}_i)$ is the OG distance (in the A norm) from $\mathbf{x}_k$ to $\mathbf{v}_i$. (5e)

Conditions necessary for a local minimum of J_m are as follows:

Fuzzy c-Means (FCM) Theorem [4]. (U,v) may minimize $\Sigma\Sigma\, u_{ik}{}^m(\|\mathbf{x}_k - \mathbf{v}_i\|_A)^2$ for m>1 only if :

$$u_{ik} = \left(\Sigma\, \|\mathbf{x}_k - \mathbf{v}_i\|_A \,/\, \|\mathbf{x}_k - \mathbf{v}_j\|_A \right)^{-2/(m-1)} \quad \text{for all } i,k \quad ; \quad \text{and} \qquad (6a)$$

$$\mathbf{v}_i = \Sigma(u_{ik})^m \mathbf{x}_k / \Sigma(u_{ik})^m \quad \text{for all } i \quad . \qquad (6b)$$

The FCM algorithms are simple Picard iteration through (6a and 6b) :

Fuzzy/Hard c-Means (FCM) Algorithms [2].

<FCM/HCM 1> : Given unlabeled data set $X = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n\}$. Fix : $1 \le c < n$; $1 < m < \infty$; positive definite weight matrix A to induce an inner product norm on $\mathfrak{R}^s$; and ε, a small positive constant.

<FCM/HCM 2>: Guess $\mathbf{v}_0 = (\mathbf{v}_{1,0}, \mathbf{v}_{2,0}, ..., \mathbf{v}_{c,0}) \in \mathfrak{R}^{cs}$ (or, initialize $U_0 \in M_{fcn}$).

<FCM/HCM 3>: For j = 1 to J:

<3a> : Calculate U_j with $\{\mathbf{v}_{i,j-1}\}$ and (6a) ;

<3b>: Update $\mathbf{v}_{i,j-1}$ to $\mathbf{v}_{i,j}$ with U_j and (6b), $1 \le i \le c$

<3c>: <u>If</u> $\max\{\|\mathbf{v}_{i,j-1} - \mathbf{v}_{i,j}\|\} \le \varepsilon$, <u>then</u> stop and put $(U^*, \mathbf{v}^*) = (U_j, \mathbf{v}_j)$; <u>Else</u> : Next j

Configuration of the Posture Control Data

The following conceptual arrangement of the data will be used in subsequent discussions. We regard the data as an array of size (p x 4000), where p=number of features (channels) used in the processing. Each column of the data matrix is thus a vector in $\mathfrak{R}^p$; and each row of the data matrix contains the observations collected by one sensor at each point in time. The data possess one of three labels; Pre(SOT)1=p1, Pre(SOT)6=p6, or Post(SOT)6=po6, so the overall data matrix for pairwise comparison of separation between any pair of these three classes is partitioned at column 2000 (the final observation time). EMG data were sampled at four times the frequency of transducer data, so we decimated the EMG data in order to align them with the transducer samples.

The basic data set for a single subject and each pair of classes thus consists of 4000 samples taken across a 20 second time interval by sensors attached to a subject at 11 locations (channels). Data were collected

2. Project Description and Technical Approach

Fuzzy c-Means

Let (c) be an integer, $1 < c < n$ and let $X = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n\}$ denote a set of (n) feature vectors in $\Re^p$. X is *numerical object data*; the j-th object in this study is a set of p measurements of sensor signals at time t. To be technically accurate, the notation for the posture control data should be something like $\mathbf{x}_j = \mathbf{x}(t_j)$, j = 1,2, ... , n; however, in the interests of clarity we will suppress the dependency of the feature vectors on time. x_{jk} is, for this data, the j-th channel value associated with time k. Given X, we say that (c) fuzzy subsets $\{u_i: X \rightarrow [0,1]\}$ are a fuzzy c-partition of X in case the (cn) values $\{u_{ik} = u_i(\mathbf{x}_k),\ 1 \le k \le n,\ 1 \le i \le c\}$ satisfy three conditions:

$$0 \le u_{ik} \le 1 \text{ for all } i,k \text{ ;} \tag{1a}$$

$$\Sigma u_{ik} = 1 \text{ for all } k \text{ ;} \quad \text{and} \tag{1b}$$

$$0 < \Sigma u_{ik} < n \text{ for all } i. \tag{1c}$$

Each set of (cn) values satisfying conditions (1) can be arrayed as a (cxn) matrix $U = [u_{ik}]$. The set of all such matrices are the *non-degenerate fuzzy c-partitions* of X:

$$M_{fcn} = \{U \text{ in } \Re^{cn} \mid u_{ik} \text{ satisfies conditions (1) for all i and k}\}. \tag{2}$$

And in case all the u_{ik}'s are either 0 or 1, we have the subset of *hard (or crisp) c-partitions* of X:

$$M_{cn} = \{U \text{ in } M_{fcn} \mid u_{ik} = 0 \text{ or } 1 \text{ for all i and k}\}. \tag{3}$$

Data structures identified by partitions which are optimal in the sense of minimizing the function defining them often provide good insights and explanations into substructure of the process that produced the data. The FCM functional is as follows:

$$J_m(U,\mathbf{v};X) = \Sigma\Sigma u_{ik}{}^m(\|\mathbf{x}_k - \mathbf{v}_i\|_A)^2 \quad , \qquad \text{where} \tag{4}$$

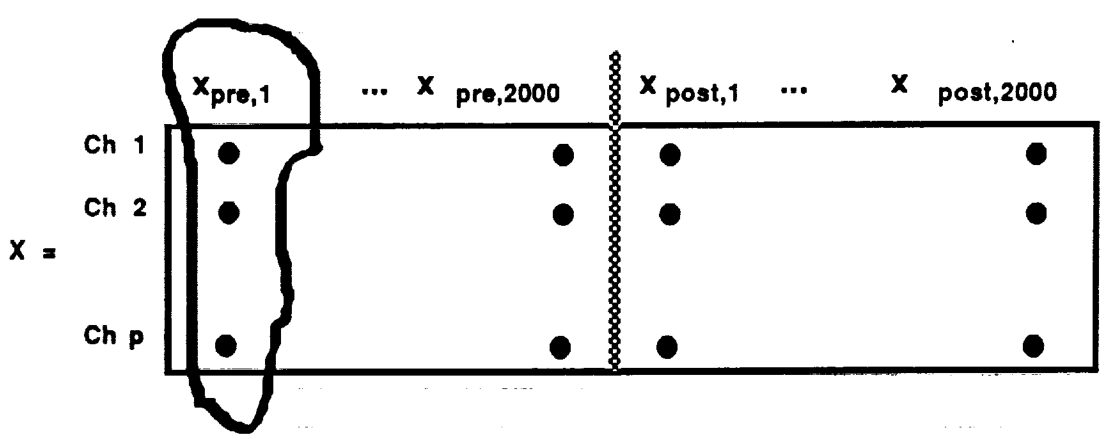
$m \in [1, \infty)$ is a weighting exponent on each fuzzy membership; (5a)
$U \in M_{fcn}$ is a fuzzy c-partition of X; (5b)
$\mathbf{v} = (\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_c)$ are cluster centers in $\Re^s$; (5c)

both before (pre) and after (post) a subject was exposed to roughly 30 minutes in the TTD with one of six trial environments (SOTs 1-6). When using FCM, rows of the data matrix X in Figure 1 correspond to features. For p=11, all of the data channels are used. Choosing, e.g., features 3,7, and 8 corresponds to reading and processing only those three rows of X. The vector $\mathbf{x}_{pre,1}$ which is highlighted in Figure 1 is a column vector with p entries : $\mathbf{x}_{pre,1} = (x_{pre,1,1}, x_{pre,1,2}, \ldots, x_{pre,1,p})^T$. It will be convenient in our discussion to identify and subscript data sets and outputs obtained on them as follows:

s_i	=	data matrix for subject (i,)	i=1,2,3,4,7;	(8)
pJ	=	SOT test (J), Pre TDD	J=1,6;	
poK	=	SOT test (K), Post TDD	K=6.	

Thus, s4p6po6 means subject 4, Pre6 vs Post6. Since our processing was all done on pairs (c=2) of labeled data sets, the three combinations that appear in our discussion are (p1, p6), (p6, po6) and (p1, po6). Conceptually, the data matrix has the following configuration:

Figure 1. Arrangement of the Posture Control Data for one subject for one trial



Feature Selection

The 11 features in X are labeled as shown in Table 1 (NASA Channel # = C):

Table 1. Posture Control Features (Channels)

Channel	Location	Data Type
1	left front transducer force	Transducer
2	right front transducer force	" "
3	shear force transducer	" "
4	left rear force transducer	" "
5	right rear force transducer	" "
7	shoulder sway bar	" "
8	hip sway bar	" "
11	soleus	EMG Signal
12	hamstrings	" "
13	tibialis	" "
14	quadriceps	" "

After several runs using all 11 channels, each of which produced uninterpretable results, we performed several statistical analyses (principle components and MANOVA) in an attempt to find transformations of the data that would give better results in 11-space. These attempts were also short lived, and seemed to produce nothing useful. Finally, we resorted to a graphical plot of the raw signals in all 11 channels, and used visual inspection to select the signal channels that seemed most likely to possess good discriminatory power. None of the EMG data seemed, upon visual inspection at least, to contain information that could be used to good advantage for classification, so we abandoned processing on these channels early in the study. The features (channels) selected for further analysis were as follows:

Feature Set 1

Channel **3** = shear force transducer
Channel **7** = shoulder sway bar
Channel **8** = hip sway bar

At the suggestion of Tom Collins, we also tried the following sets of three features:

Feature Set 2

Channels **(1+2+4+5)/4** = ave. left, right, front, rear force transducers
Channel **3** = shear force transducer
Channel **8** = hip sway bar

Feature Set 3

Channels **(1+2+4+5)/4**= ave. left, right, front, rear force transducers
Channel **3** = shear force transducer
Channel **7** = shoulder sway bar

Feature sets 2 and 3 did not seem to produce better results than Feature set 1, the channel 3-tuple {3,7,8}. We also tested all two dimensional subsets of {3, 7, 8} in an attempt to further reduce the complexity and computation time for this problem. However, none of the subsets of {3, 7, 8} yielded encouraging results. After these initial trials, all remaining experiments were conducted on the channel 3-tuple{3,7,8}.

Initialization of FCM for the Posture Control Data

Since X is pairwise labeled, we can initialize FCM in step FCM 2 with U_L, the hard partition that labels the data. Moreover, the number of classes is known, c=2. Thus, partition U_L is the 2 x 4000 matrix :

$$U_L = \left| \begin{array}{c} 1\,1\,1 \ldots\ldots 1\,1 \\ 0\,0\,0 \ldots\ldots 0\,0 \end{array} \right\| \begin{array}{c} 0\,0\,0 \ldots\ldots 0\,0 \\ 1\,1\,1 \ldots\ldots 1\,1 \end{array} \left| \begin{array}{l} \Rightarrow \text{class A} \\ \Rightarrow \text{class B} \end{array} \right. \tag{9}$$

where A and B stand for any of the three possible labels (p1, p6, po6). This initialization *can* be used, of course, with unlabeled data, but it may not lead to a "good" solution, so initialization procedures for FCM should be widened if this initial study is continued. For calculations on time subintervals, a label matrix in the form of (9), adjusted to the correct subsize, was used to initialize FCM, and was the basis for computation of the resubstitution error rate described next.

Measures of Performance and Separability

We use two performance indices to guide our analysis of the data. The primary measure of performance is the <u>observed label error rate</u> $E_L(U, X_{ij})$ for U in M_{cn}. This is computed by first defuzzifying any terminal fuzzy c-means partition, say U_{FCM}, into a hard partition by thresholding with the so-called method of α-cuts. Specifically, for a chosen membership threshold $\alpha \in [0,1]$, we define the hard label matrix U_α derived from U_{FCM} as follows:

For cols j for which $\exists$ a row i in U_{FCM} such that $U_{FCM,ij} \geq \alpha$, $u_{\alpha,ij} = 1$, $u_{\alpha,ij} = 0$, $k \neq i$; and otherwise,
For cols j for which $\exists$ no row i in U_{FCM} such that $u_{FCM,ij} \geq \alpha$, declare "no label for j"

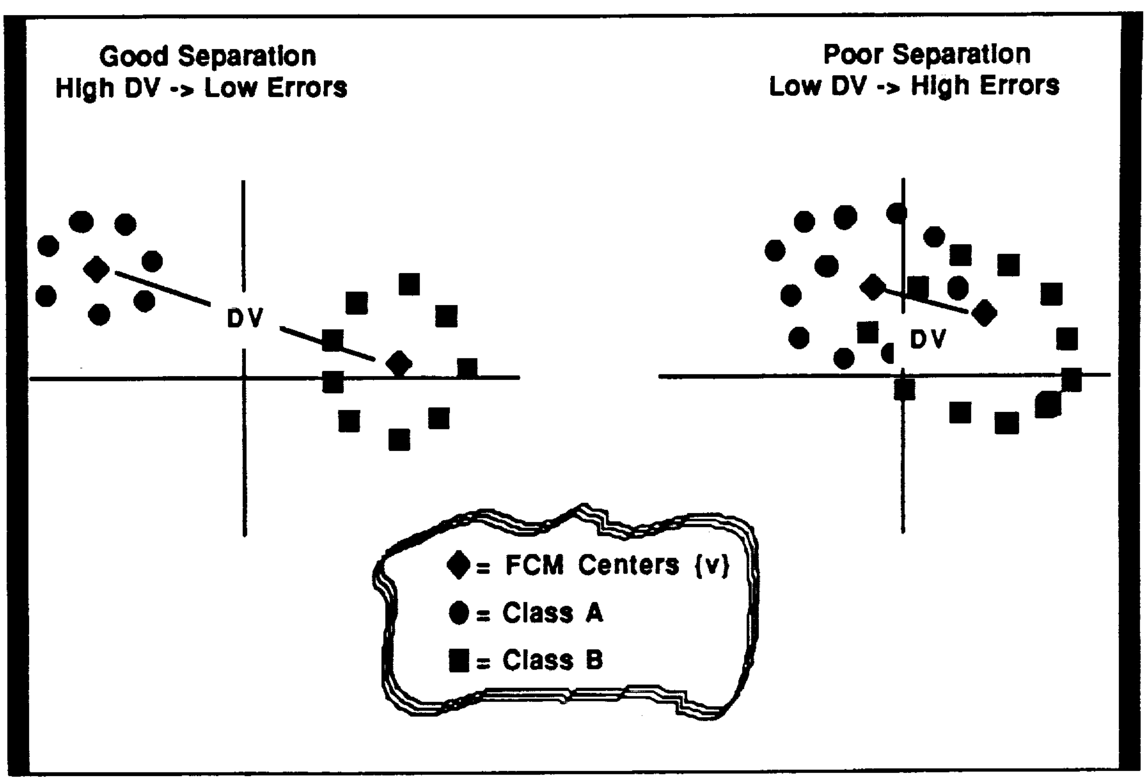
Because "no label for j" columns of U_α do not contain a "1" in any row, U_α is not, strictly speaking, a hard partition of the data. This can be accounted for in a formal way by adding a c+1-st row to U_α and U_L, with zeroes in every column of U_L, and (placed) 1's in each column of U_α where "no label" occurs. After the hard "partition" U_α has been determined, we compute the label error rate as follows:

$$E_L(U_{FCM}, X_{ij}) = \Sigma\Sigma| u_{L,ij} - u_{\alpha,ij} | /2n_L \tag{10}$$

where n_L is the number of labeled data used for the run. E_L is simply the number of times that the labels in U_α disagree with the given labels divided by the total number of trials (samples) used to generate U_{FCM}.

We also defined and tested a measure of separability of the data that is *related* to E_L, and is thus most accurately regarded as a "second order" or indirect measure of classifier performance. Such a measure is needed for detecting, in unlabeled data, when the data are being well separated, since the error rate E_L cannot be computed with unlabeled data in on-line processing during data acquisition. The measure of separation used was the distance DV between FCM cluster centers defined in (11) and illustrated in Figure 2 .

Figure 2. Geometric Rationale for the measure DV of Cluster Center Separation



Cluster Center Separation Distance between Prototypes (c=2, Euclidean Norm)

$$DV(v_{FCM,tAB}) = \| v_{FCM,t,A} - v_{FCM,t,B} \| \tag{11}$$

In (11) the variable t stands for iteration number of FCM, and may take any integer value between t=initial or t=final. It is intuitively plausible, but not mathematically necessary, that DV increase as the clusters that have $v_{FCM,t,A}$ and $v_{FCM,t,B}$ as their prototypes become increasingly well separated as t runs from initial to final. This is illustrated pictorially in Figure 2. In this sketch the data on the left, where DV is high, will be "more separable" than the data on the right, where DV is low. Thus, as DV increases, one may expect (hope!) to see a concomitant decrease in error.

Classifier Rule

The 1 NP classifier uses the FCM cluster centers as a basis for the *1 NP decision rule* defined in (12):

$$\text{Decide } \mathbf{x} \in A \quad \text{if and only if} \quad \| \mathbf{x} - \mathbf{v}_A^* \| \le \| \mathbf{x} - \mathbf{v}_B^* \| \text{ : otherwise, } \mathbf{x} \in B. \tag{12}$$

Because the memberships $u_{ik,FCM}$ are calculated with (6a) (which shows that $u_{ik,FCM}$ is inversely proportional to $\| \mathbf{x}_k - \mathbf{v}_i^* \|$), defuzzification of U_{FCM} to U_α as discussed above implicitly implements rule (12) as long as every column gets a label (again, we note that, strictly speaking, this is true only when $U_\alpha = U_{mm}$, that is, *every* column receives a "1" in the row of maximum membership (= minimum prototype distance). Thus, error rates reported below are essentially 1 NP rates, discounting those few points that do not receive labels because both memberships Uik,A and uik,B lie in the interval (.50, .60) and sum to 1.

Computational Protocols

In all of our experiments we used ε=0.01, α=0.6, c=m=2, and the Euclidean norm as the measure of distance whenever one was needed. To estimate the performance of the 1 NP classifier defined by (12), our general strategy was as follows. First, any particular data set was submitted to FCM under the protocols just listed, and FCM ran to termination, producing the final cluster centers $\mathbf{v}_{A,final}^*$ and $\mathbf{v}_{B,final}^*$. Subsequently, the matrix U_{FCM} was defuzzified using U_α with α=0.6, and the points in the data were classified (implicitly) using 1 NP rule (12); points that received no hard label (A or B) were counted as mistakes. Finally, the error rate E_L defined in (10) was calculated. Next, we proceed to a discussion of the results we obtained using the approach outlined in this section.

3. Results and Discussion

3A. Time *Subinterval* Analysis for Individual Subjects

The discussion in this section is based on the data listed in Appendix A, which contains outputs for 15 runs : 5 subjects by 3 pairwise classes. These 15 runs subdivided the data into 10 two-second time slices, and processed subinterval data sets separately. That is, we took a vertical subslice through the matrix X in Figure 1, adjusted U_o and n_L, and submitted the reduced size data to FCM. This was done over each of the three class pairs (p1, p6), (p1, po6) and (p6, po6). We had data for five subjects, numbered 1,2,3,4, and 7, for each of the three class pairings.

Figure 3, views a,b and c, shows the error rates achieved on the fifteen combinations tested in this section. The key on the right hand side of each of these figures is translated as follows: **E.s1p1p6 = Error rate for subject 1, Pre1 vs Pre6,** and so forth. As can be seen, the error rate does seem to be a function of time; that is, error rates are initially higher, and drop off after 2-6 seconds. Figure 3a shows Pre1 vs Pre6; error rates beyond t=4 seconds for these two subclasses are quite low, and this trend is maintained over all five subjects.

Figure 3a. Error Rates on all 5 subjects for Pre1 vs Pre6

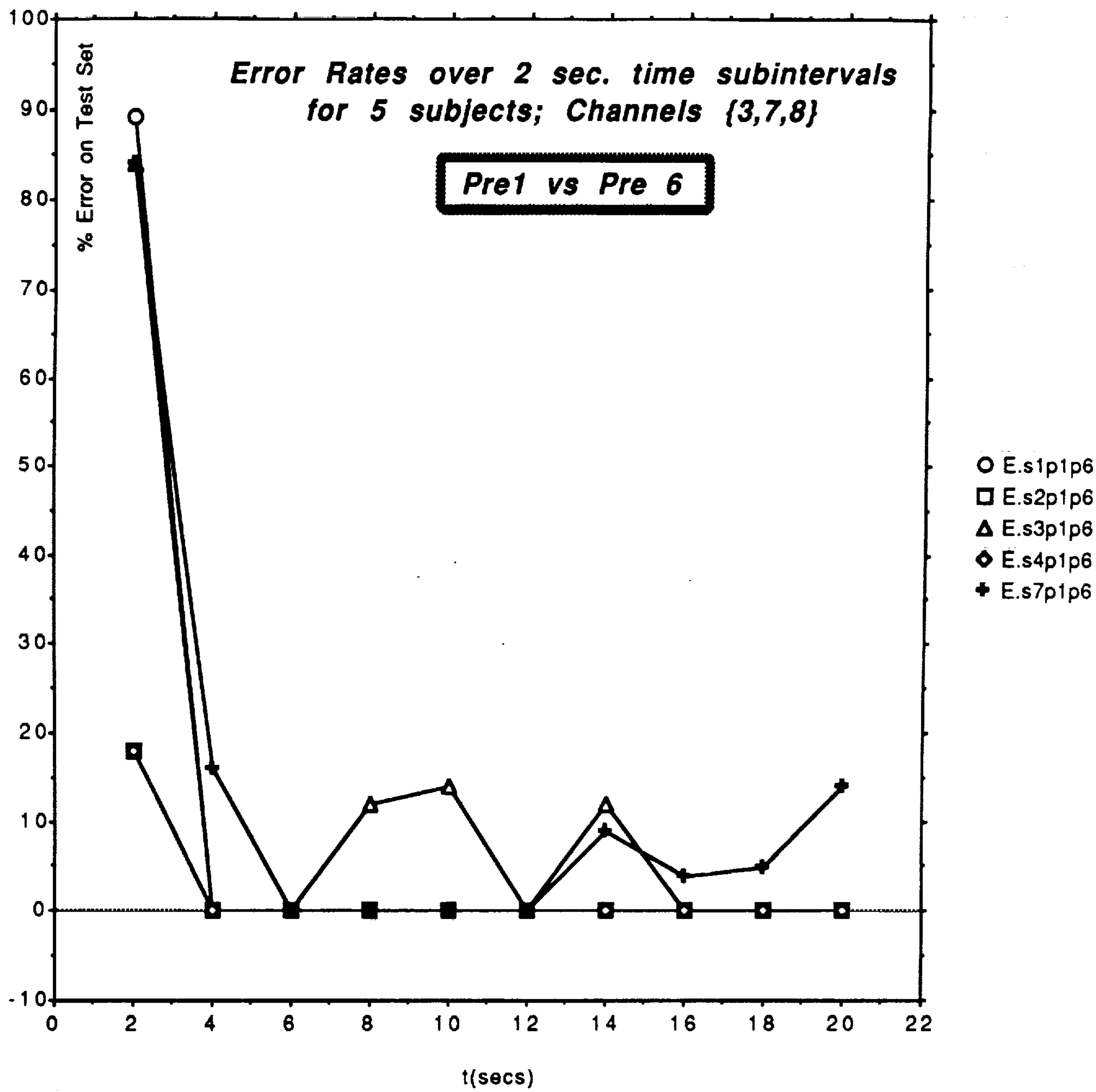
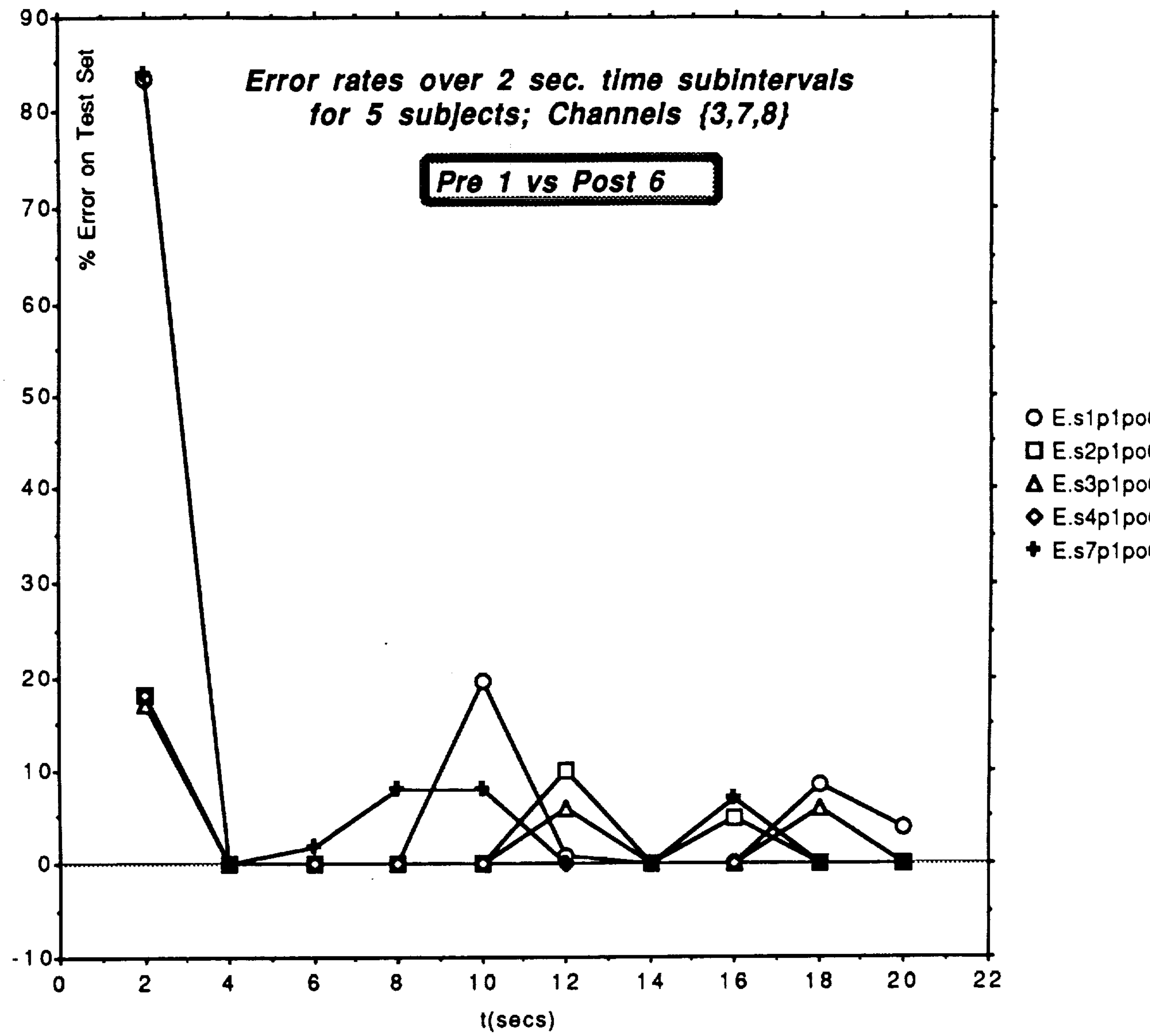
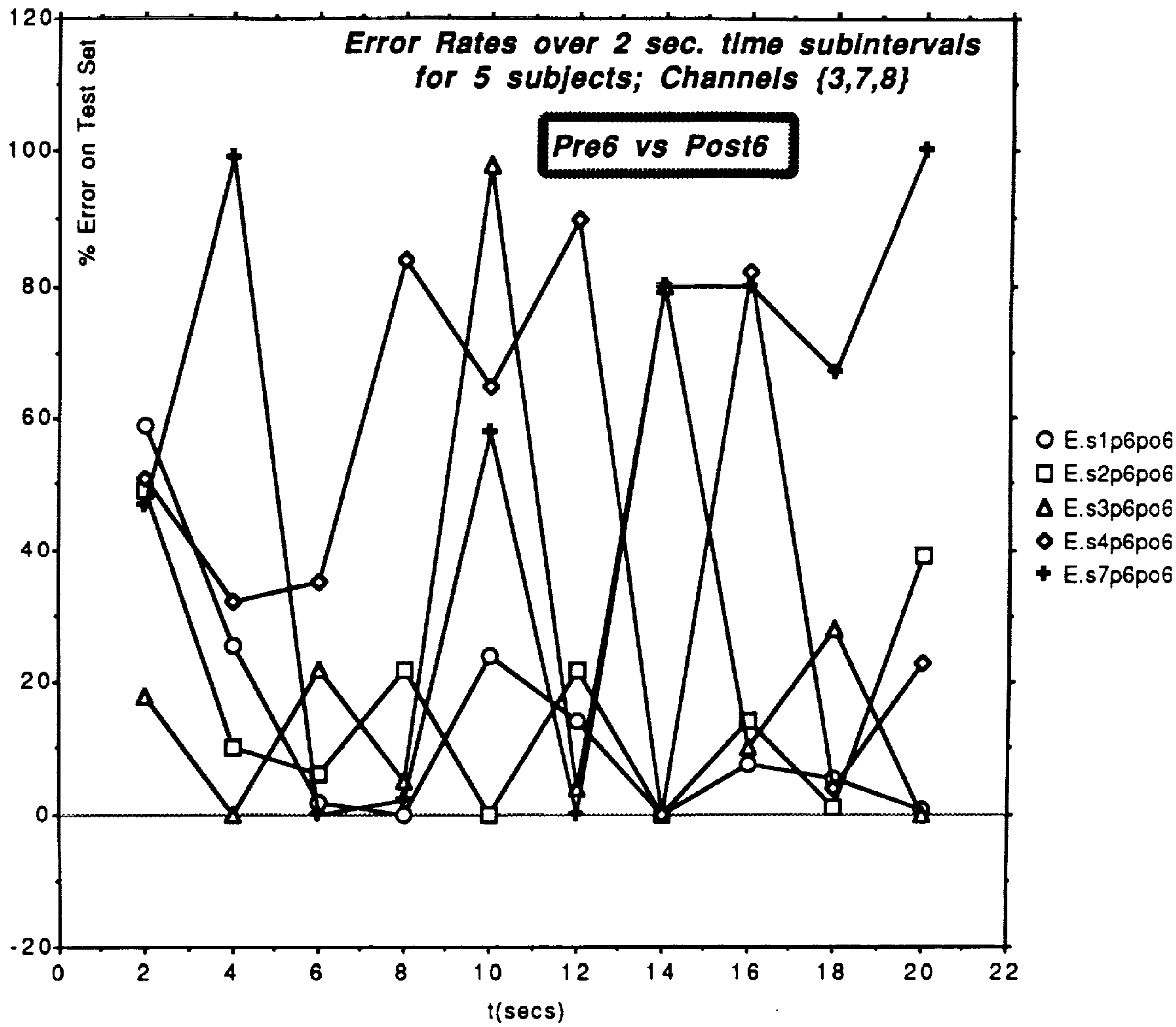


Figure 3b : Error Rates on all 5 subjects for Pre 1 vs Post 6



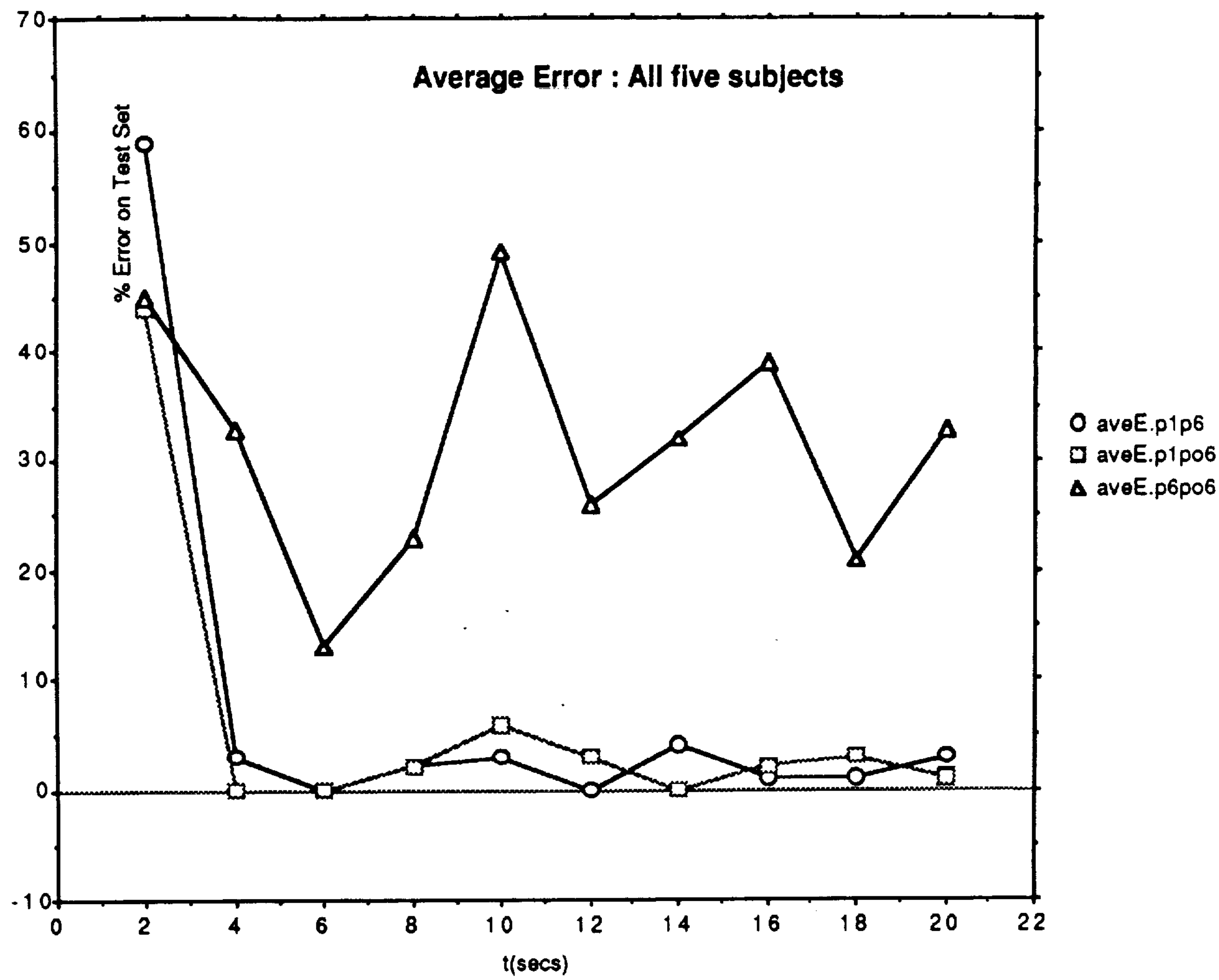
Comparing Figure 3b to 3a, we see that the trends evident for Pre1 vs Pre 6 are sustained almost exactly for the pair of classes Pre1 vs Post 6. The error rate is initially high, and after 4 seconds, drops to fairly reasonable levels. Note that the error is zero for several of the subjects over several time subintervals. This indicates that there are periods of time when the separation is perfect; one wonders if there is a physical interpretation of this algorithmic result?

Figure 3c : Error Rates on all 5 subjects for Pre6 vs Post6



Comparing figures 3b and 3a to Figure 3c, we see that the trends evident for Pre1 vs Pre6 and Pre1 vs Post6 are not well sustained. Indeed, error rates for Pre6 vs Post 6 are very high, and do not seem to follow the pattern established by the graphs in Figures 3a and 3b. Since Pre1 is common to Figures 3a and 3b, we are led to speculate that this class is much more well separated from Pre6 and Post 6 than they are from each other. This is made even clearer by examining the graphs in Figure 4, which show the *average* error rates achieved over all five subjects for each *pair of classes*. After 4 seconds, Pre1 seems to be separable from either Pre6 or Post 6 fairly readily, whereas Pre6 and Post6 continue to exhibit average errors between 13%-50% for all time subintervals.

Figure 4 : Average error rates on 2 second subintervals for each pair of classes over all five subjects.



To get an idea of the relationship between these error rates and the *subjects*, we also computed the average error rate of each subject across all 30 computational trials (10 time subintervals for each of the 3 class pairings). Table 2 shows these averages. Apparently the lowest rates are achieved with the data of subject 2; while the highest are associated with subject 7. Note that subjects 1,4, and 5 are rather close. In terms of this statistic, one is tempted to conclude that these latter three subjects responded to the simulation in a fairly uniform way, while subjects 2 and 7 seemed to make more and less stable responses, respectively. However, the sample size here is small enough to warrant great caution in accepting such generalizations.

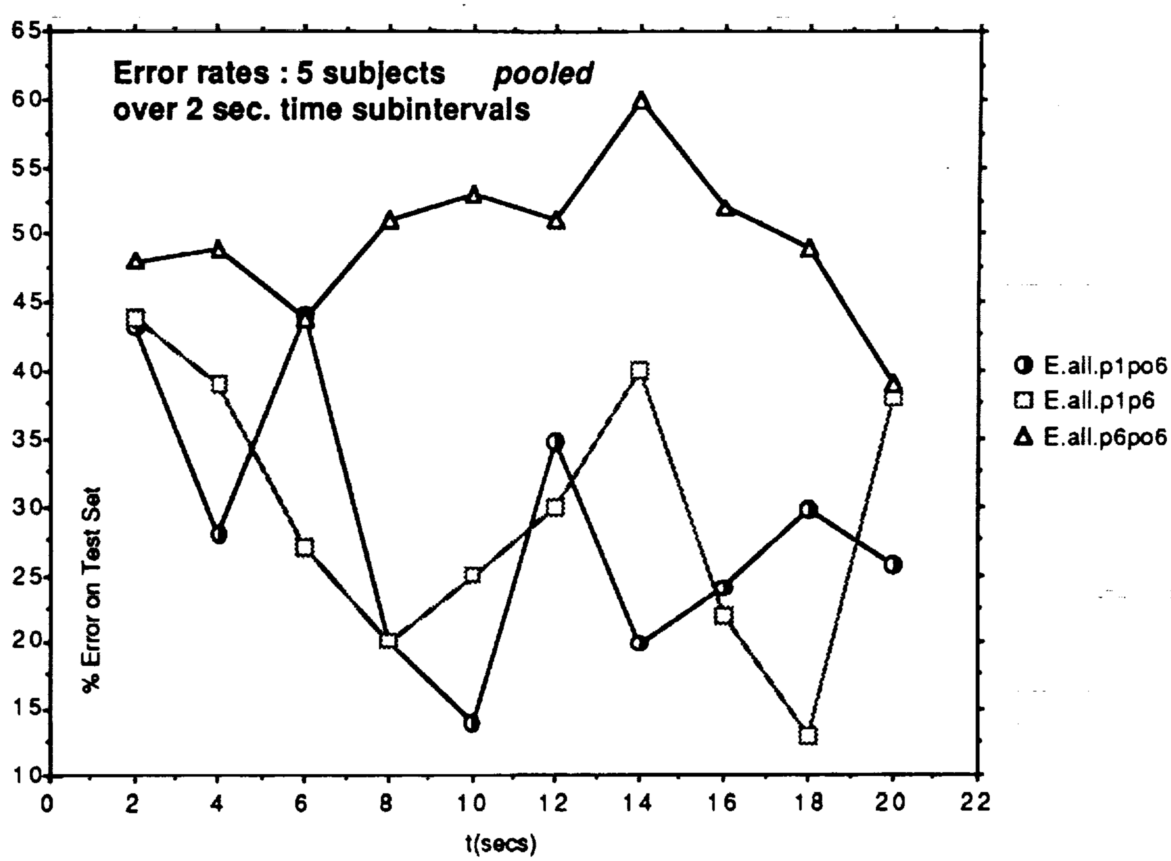
Table 2. Average error rate for each subject across 30 time subintervals

Subject	Average Error, %
1	12
2	6
3	14
4	17
7	23

3B. Time *SubInterval* Analysis for *Pooled* Subjects

To see what effect pooling data across subjects has on separability, we combined the data sets for each subinterval for all five subjects. This section is based on the outputs listed in Appendix B for 3 runs : (5 subjects *pooled* by 3 pairwise classes). Figure 5 depicts error rates obtained by plotting the data listed in Appendix B. The three graphs in Figure 5 should compared to Figures 3a=(p1p6), 3b=(p1po6), and 3c=(p6po6). This comparison will show a marked increase in error rates upon trying to separate (pairwise) any two of the three pooled classes.

Figure 5 : Errors at 2 sec. subintervals for each class pair over five subjects *pooled*.



An overall idea of the effects of pooling the data may be gained by averaging the error rates in Figure 5 across time. The average error rate for each of the curves in Figure 5 is listed in Table 3.

Table 3. Average error rates for separation of classes pairwise over 10 time subintervals, 5 subjects *pooled*.

Class Pair	Average Error, %
p1 vs p6	30
p1 vs po6	28
p6 vs po6	50

These rates show that pooling subjects yields data that are far *less* separable than that of single individuals. This remark should be weighed against our earlier observation that individual subject average error rates ranged over the interval [6%, 23%] as shown in Table 2. This further corroborates the not-so-surprising conjecture that some individuals will generate much "cleaner" data (in the sense of separability) than others; and the effect of pooling data from different subjects that have different levels of response to simulated (or real) environmental factors will be to make the separation more difficult.

3C. Analysis for *Individual* Subjects over the entire time interval

The discussion in this section is based on outputs listed in Appendices C1 and C2 for 15 runs : 5 subjects by 3 pairwise classes over all 20 seconds in time are given in C1; outputs for all five subjects pooled over all 20 seconds in time for each of the three pairwise problems are given in C2. As is obvious in Table 4, processing each subject (*or* the pooled data) across the entire time interval led to much higher error rates than those obtained using the subslice approach. Indeed, several of these rates are worse than simple coin flips. It may be the case that other parametric combinations (i.e., different choices for m, U_0, $\| * \|$, ε, α and m in FCM) would yield much better results, but we doubt it. The results shown in Table 4 are not particularly encouraging for ensemble processing across the entire time interval of data collection; either FCM is not finding structure in the data, or perhaps (and perhaps equally probable !), there just isn't much discernible structure in the data. Of course, this observation also depends heavily on the features chosen - perhaps a different combination of features (or new subjects) would provide better separation; again, we doubt it. Rather, these results further convince us that the time subslice method of analyzing these data holds more promise in unraveling data substructure than processing across the entire interval.

Table 4. Error rates in % for five subjects, individually and pooled, for separation of classes pairwise over 20 second time intervals.

Subject	p1p6	p1po6	p6po6
1	30	32	52
2	66	68	45
3	39	37	51
4	63	69	57
7	22	34	63
All 5	53	52	50

3D. Detection of Separable Epochs in Time

The subslice method is not useful in practice unless the algorithm "knows" when to rely on its classification recommendations. Recognition rates do not seem to be uniformly reliable as a function of time, as is clear from the graphs in Figure 3. Thus, it is necessary to devise a scheme for deciding, "on-line", whether or not the current (in time) results are relatively reliable. The tool proposed for this task above was the measure of separation $DV(v_{FCM,AB}) = \| v_{FCM,A} - v_{FCM,B} \|$ in equation (11), where here A and B stand for any of the three conditions Pre1, Pre6 or Post6 at either initial or final (iteration) states. We can get an idea of the feasibility of using DV for detecting the onset and offset of reliable classifier performance as a function of time by plotting $DV_{initial}$ and DV_{final} as functions of time on the same axes as the error rates achieved for any of the subslice events.

Figure 6, for example, plots both the initial and final cluster center separations between the fuzzy centroids of Pre1 and Pre6 at each time subinterval, along with the error rate achieved by using the final cluster centers as a basis for the 1-NP classifier (see equation (12)) on the test set for each subslice. It was our supposition that as DV increases, Error E decrease (refer to figure 2). One sees that this is generally the case in Figure 6. For the first two seconds of the interval, the error rate is 89 %, and **both** $DV_{initial}$ and DV_{final} are at their lowest values. The general trend in Figure 6 is that as the cluster center separation increases for either $DV_{initial}$ and DV_{final} (possibly indicating an increase in separation between the data points on which the centers are based), the error decreases (indeed, here, quite dramatically, to zero for the last 18 seconds of processing).

Figure 6. Separation DV (eqn.11) and Error rates for Subject 1 ; Pre1 vs Pre6

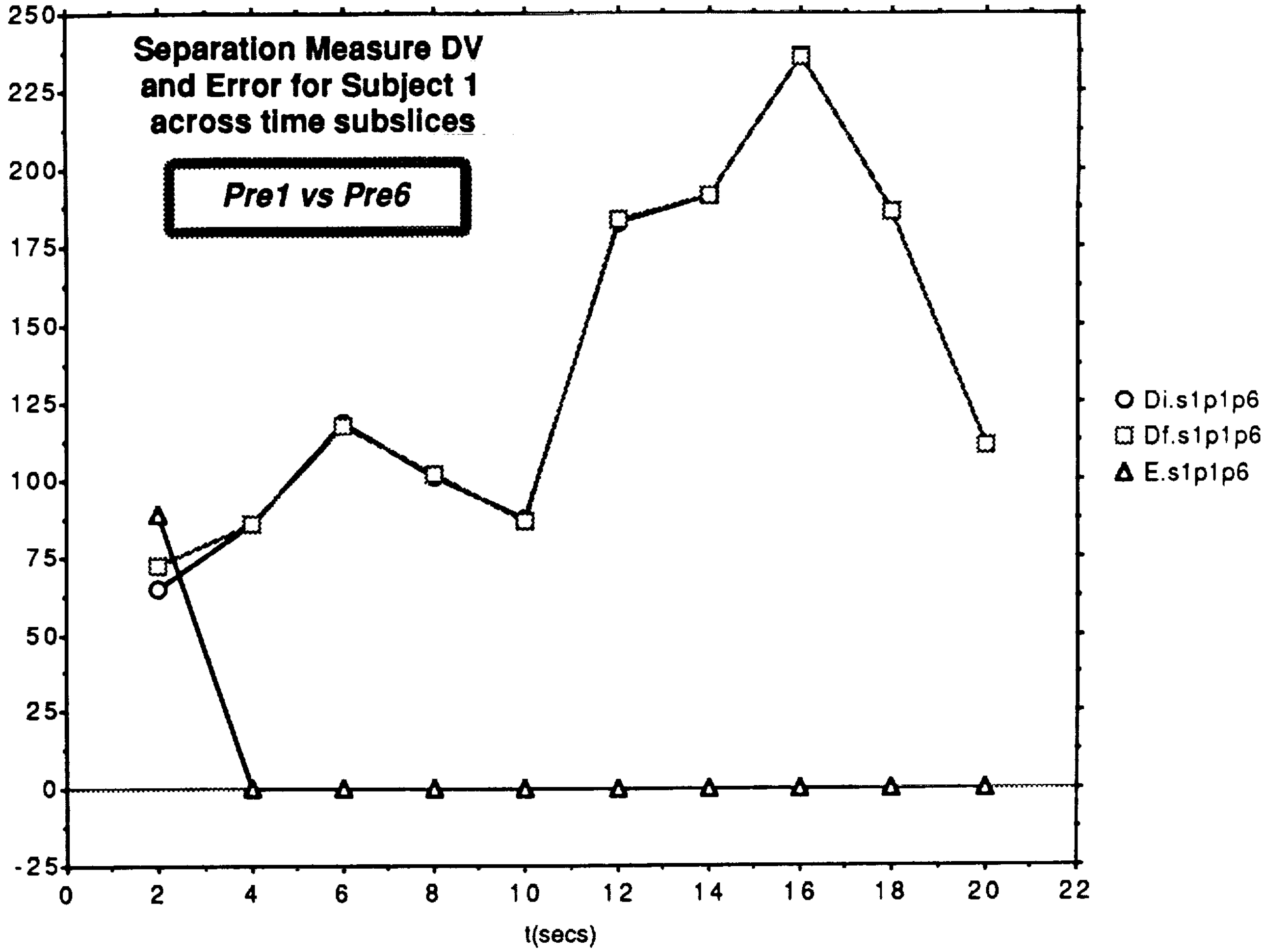


Table 5. Final Cluster Centers for Subject 1; Pre1 vs Pre6 (cf Appdx., p. A2)

TIME	CLASS	CH. 3 Shear	CH. 7 Shoulder	CH. 8 Hip
t=2	PRE1:	19.060	-61.845	-29.517
t=2	PRE6:	-34.625	-41.959	14.818
t=4	PRE1:	23.705	-65.008	-30.701
t=4	PRE6:	16.060	-13.981	37.264
t=6	PRE1:	23.744	-65.561	-32.174
t=6	PRE6:	61.983	7.321	51.964
t=8	PRE1:	23.714	-68.294	-34.123
t=8	PRE6:	37.337	-13.742	50.133

t=10	PRE1:	22.873	-66.026	-31.058
t=10	PRE6:	-34.396	-74.150	32.727
t=12	PRE1:	23.919	-58.965	-33.297
t=12	PRE6:	-128.597	-152.887	7.482
t=14	PRE1:	23.772	-58.490	-31.467
t=14	PRE6:	-139.103	-152.872	2.284
t=16	PRE1:	23.977	-57.554	-28.606
t=16	PRE6:	-178.943	-175.170	-6.380
t=18	PRE1:	23.814	-58.202	-30.091
t=18	PRE6:	-145.982	-128.452	2.090
t=20	PRE1:	23.336	-50.009	-28.295
t=20	PRE6:	-75.770	-53.719	21.706

Another point worth making in connection with Figure 6 is that the distance *between* $DV_{initial}$ and DV_{final} is itself quite small across the entire time range. This suggests that the *change* in cluster centers from their initial to final positions for this subject and pair of test conditions is slight; and that the values of the features for each centroid are relatively stable across time. The final cluster centers associated with the graphs in Figure 6 are shown in Table 5. We can gain some insight into the data by examining the evolution of the two final centers across time. Table 6, which shows the minimums and maximums from the values in Table 5, shows that the final cluster center for Pre1 is contained in a very small 3-box, that is, its deviation from some average position is quite small, about 4 units in Channel 3, 18 in Channel 7 and 5 in Channel 8. This suggests that the geometry of these three features for Pre1 is very stable over the 20 second experiment. On the other hand, the range of centroid values for the data for Pre6 is much larger: about 140 in Channel 3, 182 in Channel 7, and 58 in Channel 8. There are undoubtedly physiological reasons for the much larger deviations in the Pre6 centers; our point here is that this is what the FCM output suggests about the structure of the data across the time interval of the experiment.

Table 6. Minimums and Maximums from Table 5 for Subject 1

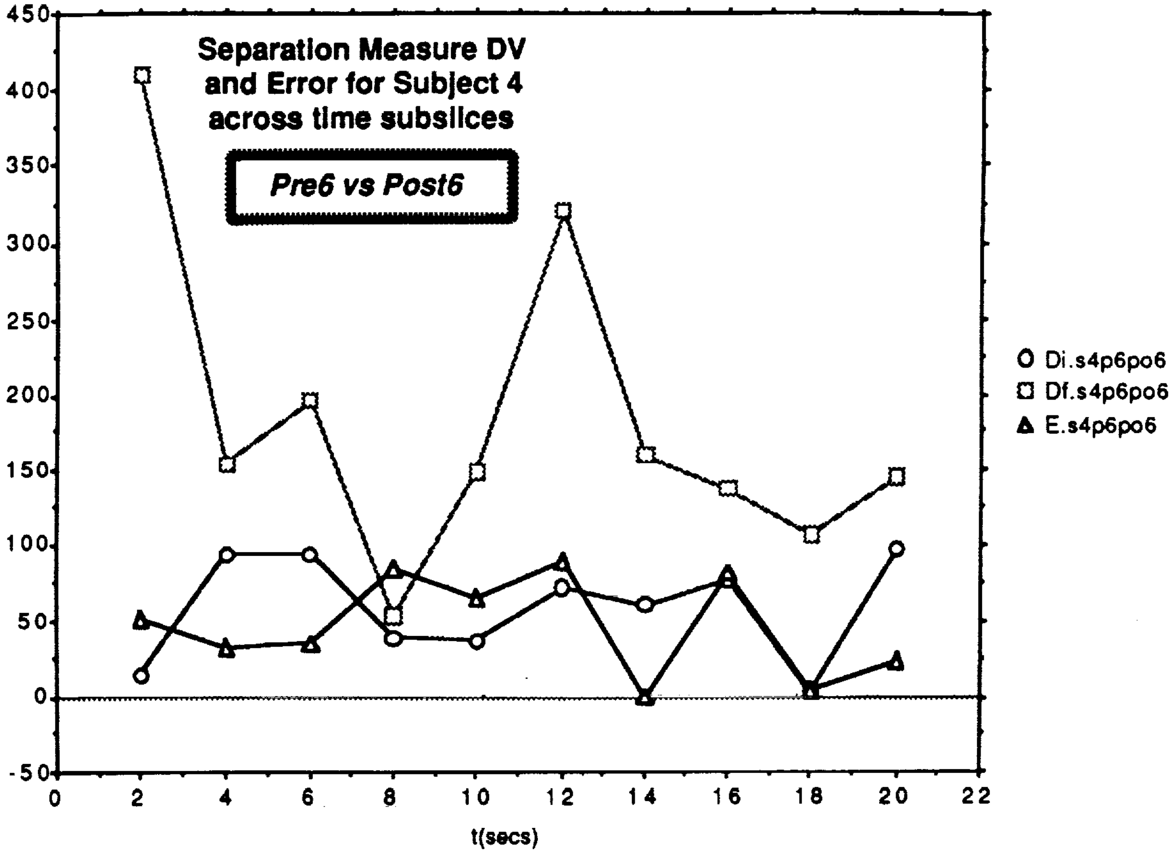
	Pre1		Pre6	
Channel	Minimum	Maximum	Minimum	Maximum
3=Shear	19.06	23.97	-178.94	61.98
7=Shoulder	-68.29	-50.09	-175.17	7.32
8=Hip	-33.29	-28.29	-6.38	51.96

We temper our enthusiasm for all these observations about trends in the cluster centers and their relationship to error rates and the data by first noting that DV does decrease from t=16 to t=20 while the error does not rise above zero in Figure 6. This suggests that there may be a threshold for DV which is useful in deciding just how much separation is necessary in order to feel fairly confident that the associated error rate is "low". This would, of course, be a necessary part of any on-line monitoring strategy based on DV anyway. In Figure 6, e.g., we might take the lowest point after t=2, which is DV=86 at t=10 as a trial threshold.

And secondly, the observations offered above are for only Subject 1 under one set of test conditions. There are 15 data sets in Appendix A that can be used to make plots and tables like Figure 6 and Tables 5 and 6, and each of these might offer different interpretations of FCM outputs. For example, an even stronger case can be made for the remarks above by looking at the outputs associated with Subject 4 (p. A5) for Pre1 vs Pre6; here, there was only an 18% error in the first two seconds, followed by no error for the rest of the time; initial and final center separations were (roughly) equal; separation values were very large (307 to 568); and the final cluster centers were again very stable, especially Pre1. It would make this report tedious to show all these figures. However, we have examined the graphs of all 15 sets, and there is much more variability in the results than our discussion indicates. For example, we can conjecture from the error rate graph in Figure 3c that subject 4, Pre6 vs Post6 will show very badly as regards the remarks made so far. To see that this is the case, we plot the results for this case in Figure 7.

From Figure 7 we see that, for this subject and comparison: (i) the error rate is *generally* lower when DV is higher, but, e.g., at t=8 DV_{final} is 52 at error = 84%, whereas 4 seconds later, DV_{final} is 320 but error=90%, (ii) there are large distances between DV from initial to final states at almost all values of time, indicating much more "mixing" of the data that are determining the centers during iteration of FCM, (iii) the centers for both classes deviate widely across time, and (iv) values of DV are pretty high (much more than the threshold mentioned in connection with Figure 6 above) but the error rate is also high.

Figure 7. Separation DV (eqn.11) and Error rates for Subject 4 ; Pre6 vs Post 6



4. Conclusions

The main results of the computations performed under this contract can be summarized as follows:

Feature Analysis. The features that worked best with the Fuzzy c-Means clustering algorithm among the ones supplied were the triple (Channel 3, Channel 7, Channel 8) = (Shear Force Transducer, Shoulder Sway, Hip Sway). Other sets, and subsets of these three gave much worse results, as did various linear combinations of the features given. In our experience the four EMG signals possessed no useful information for discrimination between pairs of tests. Certainly our choice of these features was made in a non-exhaustive way; a more thorough study of this aspect of the problem might reveal much more useful features than the ones chosen here.

Time Step Analysis. Our computations indicate that when the data for different testing conditions are treated uniformly and collectively across time, there is much more difficulty in separation than when the differential approach reported here is taken. There are some time subintervals that seem to yield data with much better separability than others. The difficulty in separating classes by processing data collected over the entire 20 seconds might be partially explained by noting that it is very hard to register the exact time that testing and/or adaptation begins, especially from subject to subject, on passing from one test state to the next; hence, the signals that generate the data are not exactly time correlated. It is tempting to assert that our differential approach identifies subintervals that correspond to physiologically interesting phenomena in the subjects tested; however, we are not well versed in this aspect of the problem, and must leave substantive conjectures of this kind to more well qualified investigators. The measure (DV) of separability we used based on cluster center distances and its utility for issues such as the stability of data (and hence, the subject generating them) have not been thoroughly explored; this is probably a good area for future concern and development. Overall, our subslice results are encouraging, but more work needs to be done before a high degree of confidence can be developed for the results reported in this pilot study.

Error Rates. It is clear from Figures 3a, 3b and 3c that, at least for the data supplied and algorithms tested, FCM *is* able to separate Pre1 from Pre 6 and Pre1 from Post6 rather well (say, at the 15% level of errors), as long as the data are treated in the time subinterval manner described herein. Indeed, the error rates shown in Figures 3a and 3b are really pretty good, and these two epochs taken together suggest that data generated by subjects in test Pre1 is rather well separated from either Pre6 or Post6. The fact that FCM worked much harder with much less success at separating Pre6 from Post6 leads us to conclude that test 6 is far more deleterious to the mechanisms guiding posture stability than test 1. Our guess here is that error rates can be brought into the 10-15 % range, but this will require a much more extensive study than we were able to perform with the resources allocated for the pilot study.

Pooling Data. Our discussion indicates that pooling data across subjects considerably degrades their separability. Although the number of subjects (5) in our pool was small, our inference from these calculations is that while separability can be achieved for a particular subject, good performance across a wide variety of subjects seems very unlikely. This is not surprising, in view of the wide variability humans have at responding to essentially identical tasks (postural adaptation in this case).

Subjects. Some idea of the relative stability of the five subjects to the tests can be gained from our results. Inspecting Figures 3a, 3b and 3c shows that subject 2 (the *squares* (□) in Figures 3a, 3b and 3c) achieved consistently lower error rates for all three data sets of pairwise tests than any other subject, and this is manifested in Table 2 by the fact that subject 2 has an overall error rate of only 6%. Subject 7, on the other hand (*plus* (+) in Figures 3a, 3b and 3c), had an overall error rate of 23%, nearly four times as high as subject 2, for the same set of computations. The suggestion here is that subject 2 has a much better adaptation mechanism to changes in his or her postural environment than, say, subject 7. This seems like a potentially important and useful suggestion - viz., that the use of FCM in this way might be a way to rank the ability of space travellers at adaptation tasks. Subsequently, such results might be used to design different individualized approaches to re-entry training for different astronauts.

Algorithms. With the limited resources at our disposal, it was impossible to spend much time testing FCM as regards different norms, initializations, termination criteria and the like. The analysis presented here is confined to classification based on only the 1 NP design. We feel that the results achieved were both reasonable and promising. There was no time to compare these results with, for example, outputs that might have been achieved with the Fuzzy Kohonen clustering algorithms or fuzzy k-means. However, the success of FCM reported herein suggests that investigations of these issues might lead to better understanding of adaptation mechanisms for postural adaptation than those currently known.

5. References

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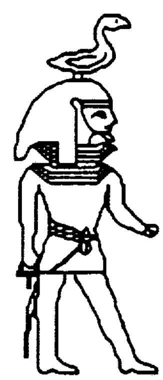
APPENDIX

CLASSIFICATION OF POSTURE MAINTENANCE DATA
WITH FUZZY CLUSTERING ALGORITHMS



FINAL REPORT

Appendix A : pp. A2-A16. Outputs for 15 runs : 5 subjects by 3 pairwise classes. The time axis is subdivided in10 equal time subslices of 2 seconds each . Only p. A2 has been "cleaned up" to show the exact meaning of the tabular outputs.

Appendix B : pp. A17-A19. Outputs for 3 runs : [5 subjects *pooled*] by 3 pairwise classes. The time axis is subdivided in10 equal time slices of 2 seconds each .

Appendix C1 : pp. A20-A22. Outputs for 15 runs : 5 subjects by 3 pairwise classes. No time slices.

Appendix C2 : p. A23. Outputs for 3 runs : 5 subjects pooled by 3 pairwise classes. No time slices.

Appendix A. Outputs for 15 runs : 5 subjects by 3 pairwise classes. The time axis is subdivided in10 equal time subslices of 2 seconds each . Only p. A2 has been "cleaned up" to show the exact meaning of the tabular outputs.

Subj1 : PRE1, PRE6 : Channels 3, 7, and 8 Filename s1p1pr6256200

Initial Entropy	Initial DV	Final DV	Final Entropy	Error Rate, %
Uo	Vo	Vf	Uf	Error
-0.000	65.4	72.4	0.368	89.2
-0.000	85.6	85.3	0.102	0.0
-0.000	117.6	117.6	0.010	0.0
-0.000	101.1	101.2	0.075	0.0
-0.000	87.3	86.1	0.136	0.0
-0.000	182.9	183.6	0.042	0.0
-0.000	191.2	191.2	0.022	0.0
-0.000	235.5	235.5	0.010	0.0
-0.000	185.7	186.5	0.043	0.0
-0.000	111.4	111.0	0.063	0.0

FINAL CLUSTER CENTERS AT TERMINATION OF FCM

TIME	CLASS	CH. 3 Shear	CH. 7 Shoulder	CH. 8 Hip
t=2	PRE1:	19.060	-61.845	-29.517
t=2	PRE6:	-34.625	-41.959	14.818
t=4	PRE1:	23.705	-65.008	-30.701
t=4	PRE6:	16.060	-13.981	37.264
t=6	PRE1:	23.744	-65.561	-32.174
t=6	PRE6:	61.983	7.321	51.964
t=8	PRE1:	23.714	-68.294	-34.123
t=8	PRE6:	37.337	-13.742	50.133
t=10	PRE1:	22.873	-66.026	-31.058
t=10	PRE6:	-34.396	-74.150	32.727
t=12	PRE1:	23.919	-58.965	-33.297
t=12	PRE6:	-128.597	-152.887	7.482
t=14	PRE1:	23.772	-58.490	-31.467
t=14	PRE6:	-139.103	-152.872	2.284
t=16	PRE1:	23.977	-57.554	-28.606
t=16	PRE6:	-178.943	-175.170	-6.380
t=18	PRE1:	23.814	-58.202	-30.091
t=18	PRE6:	-145.982	-128.452	2.090
t=20	PRE1:	23.336	-50.009	-28.295
t=20	PRE6:	-75.770	-53.719	21.706

Subj2 : PRE1, PRE6 : Channels 3, 7, and 8 Filename s2p1pr6256200

Uo	Vo	Vf	Uf	Error
-0.000	154.4	181.7	0.344	17.7
-0.000	267.2	267.7	0.030	0.0
-0.000	199.4	199.3	0.026	0.0
-0.000	203.3	203.3	0.010	0.0
-0.000	217.1	217.1	0.013	0.0
-0.000	193.6	193.6	0.035	0.0
-0.000	183.4	183.2	0.066	0.0
-0.000	212.0	212.0	0.014	0.0
-0.000	195.1	195.0	0.028	0.0
-0.000	195.5	195.5	0.031	0.0

PRE:	9.483	-81.477	-70.681
PRE:	-148.242	-117.321	12.126
PRE:	20.373	-141.840	-126.153
PRE:	-217.703	-162.127	-5.345
PRE:	20.315	-143.710	-128.074
PRE:	-115.779	-105.439	12.437
PRE:	20.360	-143.717	-129.853
PRE:	-116.514	-108.791	16.418
PRE:	20.599	-136.334	-120.235
PRE:	-153.763	-133.467	9.242
PRE:	20.529	-132.215	-120.573
PRE:	-119.587	-111.280	11.395
PRE:	20.030	-143.676	-126.207
PRE:	-55.646	-67.408	22.292
PRE:	20.218	-151.715	-132.714
PRE:	-4.837	-30.021	39.156
PRE:	20.102	-149.438	-130.907
PRE:	-64.228	-77.907	29.758
PRE:	20.620	-138.060	-125.679
PRE:	-105.913	-108.418	20.377

Subj3 : PRE1, PRE6 : Channels 3, 7, and 8 Filename s3p1pr6256200

Uo	Vo	Vf	Uf	Error
-0.000	61.1	78.0	0.158	84.0
-0.000	98.7	98.6	0.038	0.0
-0.000	133.6	133.1	0.152	0.0
-0.000	178.3	197.3	0.145	11.7
-0.000	183.6	197.1	0.182	14.0
-0.000	359.1	359.3	0.023	0.0
-0.000	187.0	199.8	0.190	12.0
-0.000	123.6	123.5	0.067	0.0
-0.000	131.8	131.8	0.022	0.0
-0.000	125.5	125.5	0.021	0.0

PRE:	18.967	0.393	-67.737
PRE:	13.347	-5.102	9.910
PRE:	19.141	-7.346	-78.040
PRE:	28.702	-12.821	20.043
PRE:	18.776	-12.251	-87.364
PRE:	-41.505	-80.797	9.577
PRE:	14.433	-18.057	-88.040
PRE:	-127.731	-135.837	-18.399
PRE:	21.448	-23.393	-90.743
PRE:	154.022	59.368	29.461
PRE:	18.766	-28.488	-106.117
PRE:	278.076	148.767	68.453
PRE:	21.388	-21.827	-96.251
PRE:	143.935	39.893	49.057
PRE:	19.021	-36.315	-107.962
PRE:	-3.180	-69.034	9.082
PRE:	18.796	-48.267	-113.306
PRE:	-35.192	-73.114	4.368
PRE:	18.992	-30.296	-98.309
PRE:	-36.218	-83.703	1.043

Subj4 : PRE1, PRE6 : Channels 3, 7, and 8 Filename s4p1pr6256200

Uo	Vo	Vf	Uf	Error
-0.000	307.3	396.3	0.280	17.7
-0.000	417.3	417.6	0.028	0.0
-0.000	369.3	368.2	0.120	0.0
-0.000	490.4	490.4	0.009	0.0
-0.000	414.9	416.2	0.101	0.0
-0.000	473.8	477.7	0.097	0.0
-0.000	567.7	567.7	0.009	0.0
-0.000	425.0	423.3	0.068	0.0
-0.000	418.0	418.0	0.014	0.0
-0.000	422.7	422.7	0.007	0.0

PRE:	9.390	-153.184	-93.468
PRE:	-354.808	-255.164	25.182
PRE:	30.340	-287.836	-180.569
PRE:	-324.040	-232.381	33.435
PRE:	28.670	-285.735	-179.356
PRE:	-76.914	-63.074	94.304
PRE:	30.004	-295.191	-186.049
PRE:	92.778	41.310	165.243
PRE:	29.352	-283.865	-177.171
PRE:	-7.627	-36.998	155.904
PRE:	27.917	-283.230	-176.478
PRE:	-400.957	-301.770	33.265
PRE:	30.483	-275.543	-183.607
PRE:	-508.186	-318.632	-9.632
PRE:	30.186	-277.983	-187.903
PRE:	-310.162	-181.422	44.595
PRE:	30.302	-294.078	-187.791
PRE:	-289.681	-192.213	61.189
PRE:	30.397	-289.404	-192.968
PRE:	-309.289	-212.007	46.553

Subj7 : PRE1, PRE6 : Channels 3, 7, and 8 Filename s7p1pr6256200

Uo	Vo	Vf	Uf	Error
-0.000	72.3	89.2	0.256	84.2
-0.000	164.2	185.3	0.209	16.5
-0.000	372.7	373.2	0.033	0.0
-0.000	251.6	251.9	0.081	0.0
-0.000	247.0	247.6	0.035	0.0
-0.000	270.4	270.4	0.018	0.0
-0.000	171.9	179.6	0.200	9.0
-0.000	184.4	189.3	0.102	4.0
-0.000	151.0	156.4	0.124	5.0
-0.000	143.8	155.1	0.185	13.7

PRE:	15.317	-64.654	-60.211
PRE:	-25.069	-25.261	8.918
PRE:	16.373	-63.218	-57.172
PRE:	119.054	57.741	38.553
PRE:	16.331	-66.166	-71.562
PRE:	279.882	150.861	79.308
PRE:	17.541	-51.518	-57.873
PRE:	195.310	73.622	69.471
PRE:	16.768	-48.517	-58.952
PRE:	177.812	93.143	64.900
PRE:	16.706	-74.185	-65.459
PRE:	184.079	89.787	69.651
PRE:	13.818	-79.578	-68.695
PRE:	75.550	32.921	57.090
PRE:	14.260	-70.564	-70.263
PRE:	-151.469	-117.752	8.293
PRE:	14.181	-73.311	-68.993
PRE:	-122.438	-94.305	4.366
PRE:	14.482	-59.094	-53.891
PRE:	78.222	44.273	42.605

Subj1 : PRE1, POST6 : Channels 3, 7, and 8 Filename s1p1po6256200

Uo	Vo	Vf	Uf	Error
-0.000	61.3	72.3	0.319	83.5
-0.000	124.9	126.8	0.146	0.0
-0.000	233.1	233.7	0.041	0.0
-0.000	225.2	226.1	0.046	0.2
-0.000	90.3	95.2	0.281	19.5
-0.000	340.2	347.4	0.098	1.0
-0.000	392.7	392.6	0.017	0.0
-0.000	353.5	353.7	0.043	0.0
-0.000	186.3	199.3	0.154	8.5
-0.000	70.4	71.2	0.136	4.0

PRE:	19.464	-70.643	-31.935
POST:	-17.126	-27.091	12.825
PRE:	23.683	-63.824	-29.502
POST:	56.654	27.780	51.834
PRE:	23.832	-65.446	-32.094
POST:	161.061	88.899	77.354
PRE:	23.939	-68.242	-34.235
POST:	162.644	64.615	85.244
PRE:	18.995	-75.831	-23.099
POST:	60.149	-58.818	61.050
PRE:	22.253	-61.346	-32.691
POST:	-194.939	-332.104	-17.828
PRE:	23.780	-58.492	-31.470
POST:	-226.069	-361.414	-34.651
PRE:	23.837	-57.680	-28.605
POST:	-241.284	-291.780	-33.968
PRE:	20.518	-63.799	-27.376
POST:	-109.380	-213.564	-6.586
PRE:	23.042	-51.398	-26.936
POST:	37.166	-61.628	42.132

Subj2 : PRE1, POST6 : Channels 3, 7, and 8 Filename s2p1po6256200

Uo	Vo	Vf	Uf	Error
-0.000	166.9	222.2	0.277	18.2
-0.000	299.9	300.1	0.027	0.0
-0.000	300.3	301.8	0.045	0.0
-0.000	187.4	185.2	0.142	0.0
-0.000	225.1	225.4	0.033	0.0
-0.000	220.2	231.3	0.171	9.7
-0.000	332.3	332.3	0.012	0.0
-0.000	226.9	232.6	0.154	4.7
-0.000	224.4	224.6	0.033	0.0
-0.000	208.5	205.8	0.155	0.0

PRE:	6.975	-73.654	-62.076
POST:	-173.367	-179.427	13.375
PRE:	20.406	-141.857	-126.179
POST:	-238.578	-218.280	4.792
PRE:	19.983	-143.750	-127.861
POST:	-247.332	-210.742	-4.803
PRE:	18.514	-143.060	-127.373
POST:	-44.126	-71.102	31.386
PRE:	20.611	-136.268	-120.112
POST:	72.346	-18.231	64.818
PRE:	17.960	-130.030	-109.432
POST:	-156.242	-203.844	23.628
PRE:	20.111	-143.706	-126.331
POST:	-274.561	-240.584	-7.090
PRE:	17.333	-149.365	-127.402
POST:	-173.840	-166.320	4.086
PRE:	20.107	-149.411	-130.871
POST:	21.014	-23.542	55.192
PRE:	18.612	-137.426	-122.241
POST:	-108.847	-132.814	39.318

Subj3 : PRE1, POST6 : Channels 3, 7, and 8 Filename s3p1po6256200

Uo	Vo	Vf	Uf	Error
-0.000	84.9	103.0	0.245	17.0
-0.000	129.3	129.3	0.008	0.0
-0.000	166.2	166.6	0.056	0.0
-0.000	205.6	206.1	0.045	0.0
-0.000	139.1	138.7	0.119	0.0
-0.000	186.2	193.2	0.158	6.0
-0.000	282.2	282.3	0.008	0.0
-0.000	212.3	214.4	0.149	0.2
-0.000	169.7	172.7	0.195	6.2
-0.000	345.0	345.7	0.038	0.0

PRE:	11.226	-0.858	-38.587
POST:	35.293	-83.311	18.338
PRE:	19.141	-7.339	-78.062
POST:	32.830	-91.517	19.192
PRE:	19.488	-11.629	-88.800
POST:	-3.552	-141.799	12.754
PRE:	19.008	-15.886	-96.465
POST:	-60.461	-180.612	-1.345
PRE:	18.840	-26.863	-98.551
POST:	-11.155	-109.231	8.958
PRE:	20.688	-29.505	-101.162
POST:	154.348	4.509	34.154
PRE:	19.095	-20.634	-106.087
POST:	241.850	44.672	54.575
PRE:	20.514	-36.402	-105.395
POST:	166.429	-8.672	49.330
PRE:	19.356	-50.218	-106.883
POST:	-52.462	-150.088	14.349
PRE:	18.823	-30.461	-98.227
POST:	-228.611	-259.449	-21.308

Subj4 : PRE1, POST6 : Channels 3, 7, and 8 Filename s4p1po6256200

Uo	Vo	Vf	Uf	Error
-0.000	295.3	375.9	0.292	17.5
-0.000	380.0	379.9	0.077	0.0
-0.000	408.7	409.2	0.052	0.0
-0.000	467.1	467.2	0.003	0.0
-0.000	416.6	416.7	0.019	0.0
-0.000	378.9	376.9	0.103	0.0
-0.000	446.2	446.2	0.016	0.0
-0.000	449.9	449.9	0.008	0.0
-0.000	453.6	453.7	0.011	0.0
-0.000	380.7	380.5	0.064	0.0

PRE:	10.021	-154.506	-94.329
POST:	-332.611	-253.073	25.064
PRE:	29.705	-287.305	-179.836
POST:	-254.969	-173.972	44.784
PRE:	30.514	-287.003	-181.469
POST:	-12.398	-6.830	113.749
PRE:	30.005	-295.166	-186.037
POST:	61.081	33.206	144.941
PRE:	30.667	-285.029	-179.567
POST:	-9.628	-13.008	133.559
PRE:	29.026	-283.049	-177.101
POST:	-180.039	-134.015	98.898
PRE:	30.478	-275.542	-183.603
POST:	-362.792	-264.268	27.003
PRE:	30.833	-278.069	-188.233
POST:	-357.592	-243.997	36.215
PRE:	30.300	-294.080	-187.793
POST:	-367.383	-250.440	26.372
PRE:	30.007	-289.061	-192.467
POST:	-229.314	-158.714	53.729

Subj7 : PRE1, POST6 : Channels 3, 7, and 8   Filename   s7p1po6256200

Uo	Vo	Vf	Uf	Error
-0.000	60.4	68.7	0.385	84.2
-0.000	129.2	130.5	0.159	0.0
-0.000	186.8	190.1	0.099	1.5
-0.000	84.2	84.2	0.226	7.5
-0.000	246.1	258.2	0.138	8.2
-0.000	359.1	359.2	0.018	0.0
-0.000	264.4	266.8	0.085	0.0
-0.000	112.2	107.2	0.232	6.7
-0.000	161.7	161.7	0.012	0.0
-0.000	128.3	131.0	0.111	0.2

PRE:	14.209	-63.657	-55.493
POST:	-8.012	-47.952	7.639
PRE:	15.818	-71.548	-67.309
POST:	-64.515	-138.890	10.440
PRE:	14.855	-66.710	-70.662
POST:	-130.494	-172.000	-7.802
PRE:	14.331	-51.944	-53.311
POST:	26.718	-22.704	24.723
PRE:	20.567	-45.662	-55.261
POST:	204.100	98.530	55.169
PRE:	16.718	-74.156	-65.446
POST:	265.011	140.836	80.188
PRE:	16.914	-82.813	-74.746
POST:	168.296	82.693	69.856
PRE:	16.472	-69.550	-66.459
POST:	-24.456	-81.103	32.052
PRE:	16.412	-74.140	-71.724
POST:	-107.580	-140.246	8.372
PRE:	15.731	-64.175	-59.795
POST:	-73.811	-132.110	7.665

Subj1 : PRE6, POST6 : Channels 3, 7, and 8 Filename s1p6p06256200

Uo	Vo	Vf	Uf	Error
-0.000	10.0	73.6	0.249	59.0
-0.000	55.0	84.7	0.252	25.7
-0.000	130.0	133.2	0.104	1.7
-0.000	151.7	154.0	0.118	0.0
-0.000	75.3	122.2	0.324	24.2
-0.000	183.8	209.4	0.172	14.0
-0.000	228.9	229.0	0.055	0.0
-0.000	134.7	141.9	0.190	7.7
-0.000	89.0	86.0	0.340	5.5
-0.000	111.9	112.9	0.132	0.5

PRE:	22.985	-52.795	-63.853
POST:	6.507	-5.859	-9.566
PRE:	38.173	14.368	-10.724
POST:	56.911	78.201	41.832
PRE:	52.115	62.898	8.259
POST:	78.435	164.274	90.692
PRE:	50.206	37.422	-13.897
POST:	85.610	164.069	66.359
PRE:	34.545	-31.859	-97.464
POST:	64.174	71.138	-38.666
PRE:	8.110	-126.567	-164.369
POST:	-24.531	-212.805	-352.414
PRE:	2.500	-139.078	-152.915
POST:	-34.938	-225.979	-361.517
PRE:	-7.013	-179.964	-179.621
POST:	-37.067	-250.540	-299.046
PRE:	1.831	-142.315	-132.890
POST:	-3.745	-92.825	-203.116
PRE:	21.636	-74.712	-54.493
POST:	41.238	36.177	-62.835

Subj2 : PRE6, POST6 : Channels 3, 7, and 8 Filename s2p6p06256200

Uo	Vo	Vf	Uf	Error
-0.000	41.0	214.4	0.148	49.0
-0.000	61.0	66.1	0.352	9.7
-0.000	166.6	175.5	0.129	6.0
-0.000	78.0	132.4	0.147	22.2
-0.000	259.2	259.6	0.032	0.0
-0.000	75.5	144.3	0.264	22.2
-0.000	280.7	280.9	0.040	0.0
-0.000	201.1	234.9	0.151	14.0
-0.000	103.8	107.3	0.182	1.2
-0.000	29.3	112.3	0.315	39.2

PRE:	1.997	-15.233	-13.777
POST:	15.616	-173.810	-157.508
PRE:	-3.003	-214.446	-165.115
POST:	2.565	-247.080	-222.412
PRE:	12.150	-118.454	-107.947
POST:	-5.712	-255.126	-216.604
PRE:	16.065	-115.322	-110.515
POST:	40.817	-2.743	-45.298
PRE:	9.098	-153.677	-133.428
POST:	64.909	72.278	-18.302
PRE:	22.941	-100.307	-112.573
POST:	13.252	-188.457	-226.432
PRE:	22.437	-55.426	-67.239
POST:	-7.122	-274.570	-240.532
PRE:	36.761	-13.626	-38.034
POST:	0.660	-195.373	-182.518
PRE:	29.723	-64.264	-78.321
POST:	55.869	23.265	-21.871
PRE:	32.095	-85.184	-101.421
POST:	24.602	-169.584	-175.248

Subj3 : PRE6, POST6 : Channels 3, 7, and 8 Filename s3p6p06256200

Uo	Vo	Vf	Uf	Error
-0.000	52.8	84.5	0.134	18.5
-0.000	78.6	78.9	0.049	0.0
-0.000	72.1	75.8	0.356	22.2
-0.000	81.4	77.1	0.418	5.2
-0.000	211.0	223.7	0.221	97.5
-0.000	208.0	216.8	0.201	4.5
-0.000	122.0	171.5	0.178	80.2
-0.000	178.1	191.5	0.182	10.5
-0.000	68.7	127.6	0.211	27.7
-0.000	260.4	262.4	0.063	0.0

PRE:	10.709	13.144	-6.716
POST:	19.629	36.992	-87.385
PRE:	20.068	28.876	-12.639
POST:	19.279	32.809	-91.445
PRE:	13.015	-22.369	-68.314
POST:	10.832	-15.078	-143.743
PRE:	-15.785	-105.785	-114.566
POST:	-2.963	-64.462	-178.455
PRE:	28.871	150.151	57.345
POST:	9.219	-6.606	-101.070
PRE:	67.641	275.982	144.857
POST:	29.891	129.561	-10.571
PRE:	32.394	73.154	-16.815
POST:	55.883	228.599	51.888
PRE:	11.340	4.602	-67.830
POST:	51.740	179.196	-0.113
PRE:	11.086	-20.703	-81.677
POST:	4.917	-98.520	-182.649
PRE:	1.063	-36.729	-84.238
POST:	-21.719	-230.012	-260.374

Subj4 : PRE6, POST6 : Channels 3, 7, and 8   Filename   s4p6p06256200

Uo	Vo	Vf	Uf	Error
-0.000	13.9	410.1	0.090	51.0
-0.000	93.6	154.8	0.249	31.7
-0.000	94.3	196.5	0.245	35.0
-0.000	38.2	52.5	0.260	83.7
-0.000	36.3	148.9	0.297	65.2
-0.000	272.2	320.4	0.277	89.5
-0.000	159.7	159.9	0.139	0.0
-0.000	76.8	137.4	0.169	82.2
-0.000	103.1	107.0	0.204	4.2
-0.000	98.2	146.2	0.154	23.0

PRE:	29.696	-360.442	-260.958
POST:	2.462	-28.933	-20.973
PRE:	31.833	-326.636	-232.861
POST:	55.396	-207.187	-137.211
PRE:	67.945	-151.150	-110.237
POST:	121.075	3.845	-1.716
PRE:	176.700	105.230	47.203
POST:	146.391	64.679	33.301
PRE:	132.687	-94.963	-92.659
POST:	150.252	21.990	-2.112
PRE:	23.585	-425.226	-315.489
POST:	101.782	-174.223	-132.335
PRE:	-10.004	-508.242	-319.024
POST:	27.522	-362.744	-264.134
PRE:	66.019	-265.223	-154.184
POST:	29.377	-365.328	-241.013
PRE:	60.774	-290.358	-192.630
POST:	25.997	-371.529	-253.215
PRE:	45.508	-302.268	-207.605
POST:	63.160	-181.965	-126.391

Subj7 : PRE6, POST6 : Channels 3, 7, and 8 Filename s7p6p06256200

Uo	Vo	Vf	Uf	Error
-0.000	36.5	69.1	0.332	46.7
-0.000	228.9	241.1	0.221	99.0
-0.000	523.2	523.9	0.037	0.00
-0.000	210.9	215.6	0.202	2.50
-0.000	18.6	93.4	0.301	58.0
-0.000	96.2	97.7	0.112	0.00
-0.000	124.8	171.4	0.256	80.2
-0.000	131.4	168.0	0.280	79.5
-0.000	52.1	82.0	0.277	66.7
-0.000	207.0	217.0	0.194	99.7

PRE:	4.053	-8.690	-11.535
POST:	17.146	-26.953	-76.906
PRE:	36.299	104.793	48.300
POST:	11.519	-57.602	-128.285
PRE:	79.450	279.526	150.657
POST:	-7.421	-127.891	-167.088
PRE:	69.540	193.872	72.718
POST:	22.092	11.250	-31.722
PRE:	42.826	134.766	49.583
POST:	65.283	205.226	106.790
PRE:	69.746	184.698	90.080
POST:	80.534	266.478	142.611
PRE:	46.496	7.984	0.683
POST:	68.883	159.604	77.550
PRE:	8.341	-139.587	-123.472
POST:	42.406	5.215	-45.241
PRE:	10.404	-67.940	-63.307
POST:	6.005	-117.679	-128.375
PRE:	40.988	69.883	39.339
POST:	8.615	-68.635	-124.655

Appendix B. Outputs for 3 runs : [5 subjects *pooled*] by 3 pairwise classes. The time axis is subdivided in10 equal time slices of 2 seconds each .

SubjALL-12347 : Channels 3, 7, and 8 Filename sallpr1po6256200

Uo	Vo	Vf	Uf	Error
-0.000	119.9	285.6	0.225	43.1
-0.000	168.9	263.1	0.298	27.9
-0.000	157.0	191.0	0.446	44.2
-0.000	175.5	212.8	0.453	20.1
-0.000	184.8	181.7	0.432	13.9
-0.000	152.2	282.7	0.387	34.8
-0.000	172.6	410.8	0.264	19.9
-0.000	194.4	333.4	0.282	24.0
-0.000	190.6	221.5	0.394	29.7
-0.000	192.0	233.3	0.351	25.7

PRE:	4.059	-48.935	-21.782
POST:	-221.068	-223.747	-2.936
PRE:	20.749	-78.073	-44.490
POST:	-207.283	-199.677	5.383
PRE:	33.126	-49.481	-30.728
POST:	-105.865	-180.518	-30.169
PRE:	1.152	-127.880	-76.368
POST:	71.928	9.453	70.062
PRE:	8.127	-110.868	-79.633
POST:	69.858	-12.627	64.252
PRE:	64.581	-43.317	-37.726
POST:	-141.921	-232.973	-1.470
PRE:	71.383	-49.897	-48.987
POST:	-265.572	-282.339	-13.440
PRE:	31.908	-83.595	-56.502
POST:	-254.880	-246.469	-7.637
PRE:	13.420	-93.235	-60.365
POST:	-169.245	-206.537	-6.573
PRE:	13.971	-87.184	-56.487
POST:	-181.327	-200.338	2.681

SubjALL-12347 : Channels 3, 7, and 8   Filename   sallpr1pr6256200

Uo	Vo	Vf	Uf	Error
-0.000	125.1	293.0	0.235	44.5
-0.000	163.7	305.4	0.250	39.0
-0.000	177.8	220.6	0.437	26.6
-0.000	182.0	233.7	0.412	20.4
-0.000	179.9	225.1	0.419	24.8
-0.000	159.4	273.8	0.431	29.9
-0.000	180.5	538.6	0.191	39.9
-0.000	196.1	231.2	0.306	22.0
-0.000	198.1	185.9	0.389	13.4
-0.000	174.3	191.4	0.420	38.3

PRE:	-1.536	-39.470	-21.310
PRE:	-236.398	-214.172	-7.594
PRE:	28.365	-51.687	-37.294
PRE:	-236.259	-200.736	-4.460
PRE:	-11.302	-104.569	-58.184
PRE:	114.833	36.740	55.004
PRE:	-12.039	-111.246	-71.587
PRE:	99.150	22.778	84.338
PRE:	-10.554	-106.231	-58.403
PRE:	116.369	38.202	58.788
PRE:	77.213	-24.277	-36.022
PRE:	-148.773	-176.426	-7.821
PRE:	13.754	-76.658	-43.356
PRE:	-472.040	-307.412	-13.828
PRE:	11.968	-85.843	-62.092
PRE:	-195.361	-163.723	4.295
PRE:	11.648	-105.501	-87.173
PRE:	-143.938	-127.349	12.306
PRE:	10.782	-72.046	-55.021
PRE:	-152.415	-150.374	7.167

SubjALL-12347 : Channels 3, 7, and 8 Filename sallpr6po6256200

Uo	Vo	Vf	Uf	Error
-0.000	24.5	346.2	0.162	48.5
-0.000	43.3	334.7	0.179	48.7
-0.000	95.8	324.3	0.313	44.3
-0.000	14.0	260.8	0.292	50.8
-0.000	35.8	234.5	0.370	52.7
-0.000	41.1	506.3	0.200	50.7
-0.000	51.4	525.0	0.233	60.0
-0.000	42.3	311.2	0.274	52.1
-0.000	40.9	272.4	0.252	49.3
-0.000	67.9	258.5	0.270	38.9

PRE:	-16.936	-37.458	11.830
POST:	-303.541	-231.363	24.960
PRE:	32.580	-21.425	30.507
POST:	-252.003	-197.288	17.649
PRE:	137.870	66.010	77.937
POST:	-112.129	-131.535	17.074
PRE:	109.729	39.131	100.931
POST:	-79.775	-114.226	8.190
PRE:	-49.798	-93.265	46.815
POST:	135.870	48.991	63.839
PRE:	216.999	96.205	64.717
POST:	-189.882	-202.650	26.154
PRE:	116.176	25.367	50.262
POST:	-312.193	-273.407	-3.910
PRE:	16.961	-49.429	31.360
POST:	-249.594	-208.397	8.298
PRE:	-64.891	-100.824	16.694
POST:	-309.789	-218.198	38.669
PRE:	-34.598	-69.214	24.837
POST:	-250.932	-210.770	23.720

Appendix C1. Outputs for 15 runs : 5 subjects by 3 pairwise classes. No time slices.

Subject: 1; PRE Trial 6 & POST Trial 6; Channels 3, 7, & 8 Filename s1pr6po6256

PRE:	45.781	39.609	-11.781
POST:	-8.414	-164.235	-217.588

Uo	Vo	Vf	Uf	Error
-0.000	48.966	294.696	0.285	52.400

Subject: 1; PRE Trial 1 & PRE Trial 6; Channels 3, 7, & 8 Filename s1pr1pr6256

PRE:	26.898	-41.442	-30.464
PRE:	2.385	-144.230	-149.346

Uo	Vo	Vf	Uf	Error
-0.000	49.415	159.057	0.184	29.850

Subject: 1; PRE Trial 1 & POST Trial 6; Channels 3, 7, & 8 Filename s1pr1po6256

PRE:	32.846	-16.908	-23.332
POST:	-24.104	-201.109	-306.028

Uo	Vo	Vf	Uf	Error
-0.000	92.494	342.185	0.178	32.200

Subject: 2; PRE Trial 6 & POST Trial 6; Channels 3, 7, & 8 Filename s2pr6po6256

PRE:	33.701	-35.718	-60.997
POST:	5.137	-202.063	-182.559

Uo	Vo	Vf	Uf	Error
-0.000	42.766	208.000	0.326	44.675

Subject: 2; PRE Trial 1 & PRE Trial 6; Channels 3, 7, & 8 Filename s2pr1pr6256

PRE:	16.898	-142.127	-125.272
PRE:	25.346	-34.309	-47.574

Uo	Vo	Vf	Uf	Error
-0.000	39.301	133.166	0.174	66.250

Subject: 2; PRE Trial 1 & POST Trial 6; Channels 3, 7, & 8 Filename s2pr1po6256

PRE:	15.715	-165.712	-152.917
POST:	44.682	9.547	-36.932

Uo	Vo	Vf	Uf	Error
-0.000	21.244	212.1 49	0.225	67.825

Subject: 3; PRE Trial 6 & POST Trial 6; Channels 3, 7, & 8 Filename s3pr6po6256

PRE:	48.476	194.163	51.269
POST:	7.243	-27.991	-100.148

Uo	Vo	Vf	Uf	Error
-0.000	73.720	271.991	0.276	51.000

Subject: 3; PRE Trial 1 & PRE Trial 6; Channels 3, 7, & 8 Filename s3pr1pr6256

PRE:	13.749	-21.681	-80.951
PRE:	54.187	216.414	101.593

Uo	Vo	Vf	Uf	Error
-0.000	92.711	302.732	0.130	39.225

Subject: 3; PRE Trial 1 & POST Trial 6; Channels 3, 7, & 8 Filename s3pr1po6256

PRE:	14.815	-26.704	-111.306
POST:	45.404	183.203	11.968

Uo	Vo	Vf	Uf	Error
-0.000	48.634	245.343	.0.182	36.825

Subject: 4; PRE Trial 6 & POST Trial 6; Channels 3, 7, & 8 Filename s4pr6po6256

PRE:	36.275	-340.879	-235.397
POST:	123.096	1.403	-9.485

Uo	Vo	Vf	Uf	Error
-0.000	53.367	419.202	0.188	57.275

Subject: 4; PRE Trial 1 & PRE Trial 6; Channels 3, 7, & 8 Filename s4pr1pr6256

PRE:	33.410	-308.842	-203.567
PRE:	121.759	20.954	-3.416

Uo	Vo	Vf	Uf	Error
-0.000	52.550	395.767	0.127	63.275

Subject: 4; PRE Trial 1 & POST Trial 6; Channels 3, 7, & 8 Filename s4pr1po6256

PRE:	33.416	-299.152	-199.565
POST:	109.861	-7.259	-8.650

Uo	Vo	Vf	Uf	Error
-0.000	99.910	357.063	0.122	69.250

Subject: 7; PRE Trial 6 & POST Trial 6; Channels 3, 7, & 8 Filename s7pr6po6256

PRE:	65.121	187.805	91.639	
POST:	12.310	-68.505	-95.068	
Uo	Vo	Vf	Uf	Error
-0.000	87.323	321.471	0.218	63.525

Subject: 7; PRE Trial 1 & PRE Trial 6; Channels 3, 7, & 8 Filename s7pr1pr6256

PRE:	16.147	-66.868	-63.267	
PRE:	64.921	182.922	89.211	
Uo	Vo	Vf	Uf	Error
-0.000	169.329	296.688	0.124	22.300

Subject: 7; PRE Trial 1 & POST Trial 6; Channels 3, 7, & 8 Filename s7pr1po6256

PRE:	14.253	-64.160	-83.155	
POST:	66.890	203.909	100.721	
Uo	Vo	Vf	Uf	Error
-0.000	92.579	329.305	0.123	34.325

Appendix C2. Outputs for 3 runs : 5 subjects pooled by 3 pairwise classes. No time slices.

Subject: 12347; PRE Trial 6 & POST Trial 6; Channels 3, 7, & 8 Filename sallpr6po6256

PRE:	48.943	59.758	-3.468
POST:	14.542	-206.936	-188.817

Initial Entropy	Initial DV	Final DV	Final Entropy	Error Rate, %
Uo	Vo	Vf	Uf	Error
-0.000	38.304	326.594	0.343	50.485

Subject: 12347; PRE Trial 1 & PRE Trial 6; Channels 3, 7, & 8 Filename sallpr1pr6256

PRE:	23.974	-224.092	-164.965
PRE:	28.097	-14.290	-39.357

Initial Entropy	Initial DV	Final DV	Final Entropy	Error Rate, %
Uo	Vo	Vf	Uf	Error
-0.000	61.728	244.563	0.330	53.315

Subject: 12347; PRE Trial 1 & POST Trial 6; Channels 3, 7, & 8 Filename sallpr1po6256

PRE:	18.521	-236.372	-197.010
POST:	31.393	-9.898	-51.288

Initial Entropy	Initial DV	Final DV	Final Entropy	Error Rate, %
Uo	Vo	Vf	Uf	Error
-0.000	54.148	269.613	0.314	52.365